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ESTIMATING THE OCCUPANCY, ABUNDANCE, AND DENSITY OF DUSKY GROUSE: DEVELOPING METHODS OF UNBIASED POPULATION MONITIORING IN MONTANA

PROJECT No. 18-636

2020 ANNUAL REPORT

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EXECUTIVE SUMMARY

This report summarizes the results of the second year (January–December, 2020) of a four-year (2019–2022) research project to develop methods for unbiased population monitoring for dusky grouse (*Dendragapus obscurus*; previously "blue grouse") in Montana. The primary objectives of this study are to 1) generate a predictive model of habitat suitability for dusky grouse throughout their range in Montana, 2) develop and evaluate survey methods that provide unbiased statewide and regional estimates of dusky grouse densities and annual trend monitoring in Montana, and 3) develop methods that facilitate rigorous and cost-effective evaluations of grouse-habitat relationships and the effects of management.

Based on our empirical estimates of local abundance and detection from spring surveys in 2019, we conducted statistical simulations to evaluate the efficacy of potential survey protocols for monitoring dusky grouse. Based on discussions in 2018 with MFWP Region 3 personnel, an acceptable monitoring program should produce unbiased estimates of abundance and annual estimates should have a coefficient of variation (CV) of the estimator of less than 15%. Results of our simulations using N-mixture models indicated that 4 replicate surveys at 360 independent survey sites yielded unbiased and acceptably precise (< 15% CV) estimates of regional abundance when local abundance was at least 0.36 individuals and the average probability of detection was 0.28.

We expanded our pilot study evaluating survey methods for unbiased monitoring of dusky grouse populations from Region 3 to include suitable dusky grouse habitat in the western half of Montana in Regions 1-5. Based on the results of our simulations, we modified 2020 survey methods from those used in 2019. Surveys were still designed so that multiple statistical methods (e.g., N-mixture models, distance sampling) could be used to estimate occupancy, local abundance, and density of dusky grouse. Survey methods consisted of point-counts with electronic playback to increase detections, and walking transect routes. Potential survey transects were randomly generated in areas identified to have high relative likelihood of dusky grouse occurrence as predicted by the model of relative habitat suitability we developed in 2019. Project personnel, volunteers, and MFWP field biologists selected a total of 60 survey transects to survey in each region. Survey transects consisted of 6 independent survey points spaced 400 meters apart along a road or trail. Surveys were only conducted during the spring breeding season from April 10 – May 29 when vocalizations of male grouse are greatest. During the survey period, a total of 291 transects were surveyed, with 59 transects surveyed in Region 1, 64 in Region 2, 65 in Region 3, 64 in Region 4, and 36 in Region 5. Of those 291 transects, at least 2 were only partially surveyed due to equipment failure. In total, 1,744 points occurring along the 290 transects were surveyed; 1720 were surveyed 4 times, 16 were surveyed only 2 times, and 8 were surveyed only 1

We used single season N-mixture models to produce preliminary estimates of local abundance and probability of detection with the 2020 spring survey data. The probability of detecting a dusky grouse was consistent across FWP regions and averaged 0.21 ± 0.03SE (CV = 14%). Estimated local abundance varied by FWP region; local abundance varied from 0.12 ± 0.03 (CV = 25%) in Region 4 to 0.56 ± 0.13 in Region 2 (CV = 23%).

ESTIMATING THE OCCUPANCY, ABUNDANCE, AND DENSITY OF DUSKY GROUSE: DEVELOPING METHODS OF UNBIASED POPULATION MONITIORING IN MONTANA

2019 Quarter 1 Report

OBJECTIVES

Objective 1: Generate a predictive model of habitat suitability for dusky grouse throughout their range in Montana

Accomplishments

We obtained dusky grouse observation data from the Integrated Monitoring in Bird Conservation Regions monitoring program (IMBCR) administrated by the Bird Conservancy of the Rockies. We previously obtained data from Spring 2009 through Spring 2018 for a total of 20,009 surveys conducted over 5,845 sites (Pavlacky et al. 2017, Hanni et al. 2018). In 2020, we updated our data with observation data from 2019 and 2020 for additional 3,441 surveys.

We updated our previous geospatial datasets in order to define annual habitat conditions. We downloaded LANDFIRE geospatial data for vegetation type, vegetation canopy cover, vegetation height, forest canopy cover, and forest canopy height for 2008, 2010, 2012, 2014, and 2016. We grouped our IMBCR observation survey data by years and associated each group of years with the appropriate land cover dataset. We grouped 2009 data with the 2008 landcover data, the 2010 & 2011 data with the 2010 landcover data, the 2012 & 2013 data with the 2012 landcover data, the 2014 & 2015 data with the 2014 landcover data, and the 2016-2020 data with the 2016 land cover data. Within their groups, we reduced the IMBCR point counts to detected/not-detected data for dusky grouse, that we then used to represent used (detected) and available (not-detected) sites. It is possible for birds to be present but not detected at available survey sites. We assumed that all dusky grouse detected at a given point count location were located within 250 m of the survey site.

Using remotely-sensed geospatial datasets, we extracted habitat information within a 250-m buffer drawn around each survey site. We used digital elevation models (DEMs) from U.S. Geological Survey, ArcGIS 10.3.1 (Environmental Systems Research Institute, Redlands, CA) and geospatial modeling environment (GME) to measure average elevation, aspect, and slope of the 250 m radii area (Beyer 2015, U.S. Geological Survey 2017). We calculated the average distance of the 250 m radii area to the nearest stream and to the nearest road using the spatial analyst tools of ArcGIS applied to the Montana Spatial Data Infrastructure (MSDI) Transportation Framework and Hydrography datasets downloaded from the Montana state library and GME (Beyer 2015, Montana Spatial Data Infrastructure 2017, 2018). We used the 2008 LANDFIRE, 2010 LANDFIRE, 2012 LANDFIRE, 2014 LANDFIRE, and 2016 LANDFIRE vegetation datasets with a spatial resolution of 30 × 30 m (LANDFIRE 2012), including layers for existing vegetation canopy (EVC), existing vegetation height (EVH), existing vegetation type (EVT), forest canopy cover (CC), and forest canopy height (CH). EVC is the vertically projected percent cover of the live canopy layer; EVH is the average height of the dominant vegetation; EVT is the type of plant community present; CC is the percent cover the tree canopy in a stand; CH is only provided for forested areas and is the average height of the top of a vegetated canopy (LANDFIRE 2012). We used GME to calculate the proportion of vegetation cover within 250 meters of the survey location (Beyer 2015). From these layers we extracted geospatial habitat information for a total of 167 variables that were then used to build resource selection functions (RSF).

We are in the process of evaluating habitat use with resource selection functions that are calibrated using general linear mixed models with a logistic link function and binomial error distribution using the lme4 package in program R (Bates et al. 2015, R Core Team 2017).

Goals for Next Quarter

Next quarter, we will finish evaluating habitat use with resource selection functions. In addition, we will expand the habitat modeling to include machine learning approaches like Random Forest. We will use an ensemble approach to estimate model-averaged predictions of habitat suitability and calculate available habitat of dusky grouse by region in Montana. We will draft and submit a manuscript for publication in a peer-reviewed journal.

Objective 2: Develop and evaluate unbiased survey methods that provide statewide and regional estimates of dusky grouse densities and annual trend monitoring in Montana

Accomplishments

<u>Methods</u>

Simulations

To evaluate survey effort required to achieve useful annual estimates of dusky grouse abundance from point-count survey protocols, analyzed using N-mixture models, we developed and modeled simulated datasets based on empirical estimates of abundance and detection probabilities from our 2019 spring survey effort. Initial simulation sets (McNew et al. 2019) examined estimates for abundance and detection based upon the 2019 survey protocol: 3 replicated visits at 100 independent survey sites located off trail. We simulated data using a "best case" scenario using an estimate of detection probability, 0.28 ± 0.10 SE, produced from the N-mixture model for spring point-counts conducted with the use of electronic playback, and our high estimate 0.48 ± 0.20 for abundance. After examining the results of simulations using the 2019 survey protocol, we then evaluated whether estimator precision could be increased by 1) increasing the number of replicate survey visits per point, and 2) increasing numbers of independent survey points. The results of these initial simulations indicated that a minimum of 500 independent survey sites with 3 replicate visits would be needed to achieve unbiased and relatively precise (<15% CV) estimates of regional population abundance (McNew et al. 2019). After reviewing the results of our initial simulations, we continued to explore alternative protocols.

We evaluated simulated model sets based on varying number of visits and varying number of independent points. For our first set of simulations, we evaluated simulated datasets based on 100 independent survey points per region with increasing numbers of replicate visits under the "best case" scenario for estimates of detection and abundance. Next, we varied the number of visits between 3–9, and the number of survey points from 100–360. For these simulations, abundance and detection were based on empirical estimates from the 2019 spring survey effort achieved using the estimates from the electronic playback survey methodology; an estimate of detection probability of 0.28 ± 0.10 SE, and an estimate of abundance of 0.36 ± 0.13 (McNew et al. 2019). We conducted simulations in the Bayesian framework where the variation in local abundance was described with a Poisson distribution, and the variation in detection was described by a binomial random process:

$$\widehat{N}_i \sim Poisson(\lambda)$$

$$y_{i,j}|\widehat{N}_i \sim Binomial(\widehat{N}_i, p)$$

Our simulation approach was like that described in the 2018 and 2019 Annual Reports (McNew et al. 2018, McNew et al. 2019). Simulations and analyses were conducted in R using the function *jags* from the 'jagsUI' package (Kellner 2019, R Core Team 2017). We used vague priors that provided little information about the estimated parameters. We used a standard vague prior (0.005, 0.005) for lambda, and a uniform distribution with a minimum of 0 and a maximum of 10 for *p* (Kery and Schaub 2012).

In the simulations we estimated the total number of individuals across all sites by summing the estimated number of individuals at each survey site. We ran three chains of length 40,000 after a burn-in period of 10,000 and thinned the posterior chains by 100 to ensure independence. We assessed convergence using the Gelman-Rubin ($\widehat{\mathrm{R}}$) statistic, which examines the variance ratio of the Markov chain Monte Carlo (MCMC) algorithm within and between chains across iterations (Gelman and Rubin 1992). We accepted parameter estimates when they came from Markov chains with $\widehat{\mathrm{R}}$ between 1.0 and 1.01.

To quantify bias of estimates for each survey protocol scenario, we ran 400 iterations of each data simulation and subsequent analysis from these iterations, we calculated the difference between the estimated local abundance ($\widehat{\mathrm{N}}_{\mathrm{i}}$) and the true abundance known for the simulated site (N_{i}). Similarly, we quantified bias in the total estimated population size by calculating the difference between Total $\widehat{\mathrm{N}}$ estimated as $\sum \widehat{\mathrm{N}}_{\mathrm{i}}$ and the true known total abundance for all sites ($\sum \mathrm{N}_{\mathrm{i}}$). We compared the posterior distributions of the mean differences between each estimate and the true values across all 400 simulations to evaluate the bias of each estimate. We considered an estimate to be clearly biased in the 95% credible interval (CrI) of the differences did not include 0. In addition, at each of the 400 iterations, we estimated the precision of each estimate by calculating the coefficient of variation ($\mathrm{CV} = \frac{\text{estimated standard error}}{\text{mean parameter estimate}}$). We evaluated the posterior distributions of the 400 derived CV estimates to determine whether survey protocols yielded acceptable levels of precision for average local abundance and total population size. We estimated probability that the average coefficient of variation would meet the manager-determined threshold of 15% by calculating the proportion of the total posterior distribution density greater than 0.15.

Spring Surveys. — During the first quarter of 2020, we evaluated different potential survey protocols using simulated datasets and N-mixture models in order to determine the survey effort required to achieve useful annual estimates of dusky grouse abundance using point-count survey protocol and electronic playback. Through simulations described above, we determined that 360 independent points with 4 replicate surveys should, on average, provide annual estimates of dusky grouse abundance with the desired level of estimator precision of <15%.

We randomly generated potential survey transects using ArcGIS and a model of relative habitat suitability (McNew et al. 2018; Figure 1). Survey transects consisted of 6 points along a road or trail, spaced 400 m apart to ensure independence (though the traveled distance along the trail/road may be greater than 400 m). The first point for transects along trails was randomly placed between 100-200m from the trailhead. The first point for transects along roads was 100m from the parking location. Field biologists selected among a randomly-generated set of potential transects and conducted surveys during 10 April – 30 May.

Surveys consisted of a total of four four-minute independent point counts at each point location along the transect. Two of the four independent point counts occurred as the observer traveled from the start to end of the transect, then a 10 minute break occurred, and two additional point counts occurred as observers traveled from the end to the beginning of the transect. Each pair of point counts was conducted one right after the other; with ≤ 1 minute between them. This yielded a total of 4 point-counts per point in one morning. In this way, a transect only needed to be visited once, while still achieving 4 replicate surveys at each point. To increase detections of male dusky grouse, each four-minute point count occurred with female calls played electronically through a portable music player or cell phone and speaker (SanDisk 8 GB Clip Jam Mp3 Player, JBL Charge 3 speaker; Stirling and Bendell 1966). The female calls consisted of a four-minute recording that consisted of a female cackle and cantus. Playback recordings consisted of alternating playback of 30 seconds of calling and 30 seconds of silence until the entire four minutes of survey had elapsed. Each 4-minute survey was treated as an independent sample and all grouse observed were recorded during each period. The distance to each observed grouse was measured with a laser rangefinder and recorded. All dusky, ruffed, and spruce grouse observed (visually or auditorily) during transit to and between survey points were also recorded and perpendicular distances to the transect recorded.

Analyses – We used single season N-mixture models to estimate local abundance and probability of detection for the spring 2020 survey data (Royle et al. 2004). We used the *pcount* function in the R ‘unmarked’ package to evaluate N-mixture models in a frequentist framework (Fiske and Chandler 2011, R Core Team 2017). We first checked the data for evidence of overdispersion by comparing null models with poisson distribution, zero-inflated poisson distribution, and negative binomial distribution for abundance. We evaluated the three different null models using Akaike’s Information Criterion (AIC; Burnham and Anderson 2002). If the models with the zero-inflated poisson distribution or negative binomial distribution had the lowest AIC value, then the data was considered overdispersed.

After testing for overdispersion, we used the distribution from the most supported null model to evaluate effects of region (FWP Region1-5), habitat suitability (medium high or high), and transect type (transect that occurred along a road or a trail) on local abundance. We evaluated support for the different models using AIC (Burnham and Anderson 2002). After determining the most parsimonious model, we used a parametric bootstrap goodness of fit test from the R ‘AICcmodavg’ package to evaluate how well the top model fit the data (Mazerolle 2017, R Core Team 2017). If the top model fitted the data well, we estimated lambda using the *predict* function and *p* using the *backTransform* function from the R ‘unmarked’ package (Fiske and Chandler 2011, R Core Team 2017).

<u>Preliminary Results</u>

Simulations

We used empirical estimates for detection and abundance from the spring 2019 survey data to evaluate the efficacy of a variety of survey protocols. For the first set of simulations, we used an estimate of detection, 0.28 ± 0.10SE, produced from the N-mixture model for point counts conducted with electronic playback, and our high estimate of abundance 0.48 ± 0.20. Results from the first set of simulations indicate that if only 100 independent sites are surveyed, a minimum of 8 replicate visits would be needed to yield unbiased and relatively precise (< 15%) indices of regional population abundance if site specific abundance is closer to our high estimate of 0.48 birds per survey point (Table 1).

For our second set of simulations we used an estimate of detection, 0.28 ± 0.10, and an estimate of abundance, 0.36 ± 0.13, produced from the N-mixture model for point counts conducted with electronic playback (McNew et al. 2019). We varied the number of independent sites from 100 to 360, and the number of replicate visits from 3 to 9. The models for many of these potential protocols produced convergence errors for site-level abundance estimates. Protocols that yielded unbiased and relatively precise (<15% CV) indices of regional population abundance while having relatively few convergence errors were 200 independent sites with 6 replicate visits, 300 independent sites with 4 replicate visits, and 360 independent sites with 4 replicate visits (Table 1).

To examine the feasibility of each of these potential protocols that yielded relatively precise results, we calculated how many survey mornings would be needed if we had 5 or 6 points per transect, and 3 or 4 replicates occurring in one morning. We calculated that if we conducted surveys at 200 independent sites with 6 replicate visits, we would need 68–80 mornings to reach our survey goals. If we conducted surveys at 300 independent sites with 4 replicate visits, we would need 50–60 mornings, and if we conducted surveys at 360 independent sites with 4 replicate visits, we would need 60–72 mornings. From this, we recommended a survey protocol of 360 independent sites with 6 survey points per transect and 4 replicate visits for the Spring 2020 season for each FWP region with dusky grouse habitat. We also recommend continuing this survey protocol for the spring 2021 season to ensure sufficient data for future simulations for evaluating potential protocols that may be more feasible for annual monitoring.

Spring Surveys.— During the spring survey period a total of 291 transects were surveyed, of which 2 were only partially surveyed due to equipment failure. 59 transects were surveyed in Region 1, 64 in Region 2, 65 in Region 3, 64 in Region 4, and 39 in Region 5. Surveys were conducted by a mix of MSU project personnel, FWP staff, and volunteers. Overall, 53 people assisted in completing the surveys, with several people completing surveys in multiple regions. In Region 1, 10 people conducted surveys, 19 people conducted surveys in Region 2, 15 people conducted surveys in Region 3, 12 people conducted surveys in Region 4, and 15 people conducted surveys in Region 5. Surveys occurred during10 April – 29 May, with the majority (90%) of surveys in occurring May.

All survey transects were located in areas predicted to be suitable for dusky grouse by our habitat model. In Region 1, we detected dusky grouse at 37 (10.4%) of 354 survey points (Table 2). In Region 2, dusky grouse were detected at 79 (20.6%) of 384 points (Table 2). In Region 3, we detected dusky grouse at 37 (9.5%) of 391 survey. In Region 4, dusky grouse were detected at 25 (6.5%) of 384 points. 384 points were surveyed and 6.5% were occupied by dusky grouse (Table 2). In Region 5, only 231 points were surveyed, and dusky grouse were detected at 41 (17.7%) of the survey sites (Table 2). The maximum number of dusky grouse detected during a single point-count was 4, and the minimum was 0 (Table 3). The average number of dusky grouse observed at each point was 0.12 ± 0.39SD in Region 1, 0.027 ± 0.59SD in Region 2, 0.12 ± 0.40SD in Region 3, 0.07 ± 0.26SD in Region 4, and 0.25 ± 0.66SD in Region 5 (Table 4).

Estimated abundance. –We found evidence that observation data from the point-count surveys were overdispersed (Table 5) and used a negative binomial distribution for all subsequent N-mixture models based on the point counts. We found the top model from our model set with covariates for abundance was a constant probability of detection and abundance varying among FWP region (Table 6). Using a goodness of fitness test with 500 simulations, the p-value for the top model was 0.35 and c-hat was 1.02 indicating a good model fit (Figure 1). Under the top model, abundance varies among FWP regions, the probability of detecting a dusky grouse was $p = 0.20 \pm 0.03$SE (Table 7). Local abundance varied among regions with the lowest abundance in Region 4 (0.12 ± 0.03SE) and the highest abundance per point count in Region 5 (0.56 ± 0.13SE; Table 7, Figure 2).

Goals for Next Quarter

We will evaluate N-mixture models for the transects and evaluate distance sampling for the point count data and the transect data. After preliminary analysis, we will create a plan for further evaluating the effects of covariates on probability of detection and abundance. Future work in 2021 will evaluate the utility of open population N-mixture models for estimating regional changes in population sizes annually. We will also plan and coordinate survey efforts for 2021.

Objective 3: Develop methods that facilitate rigorous and cost-effective evaluations of grouse-habitat relationships and the effects of management (e.g. timber harvest)

Accomplishments

For effort/accomplishments, reference objective 2.

Goals for Next Quarter

For goals for next quarter, reference objective 2.

Figure 1. Results of a goodness of fit test for the model where probability of detection (*p*) was held constant and abundance varied among FWP regions for the 2020 dusky grouse surveys.

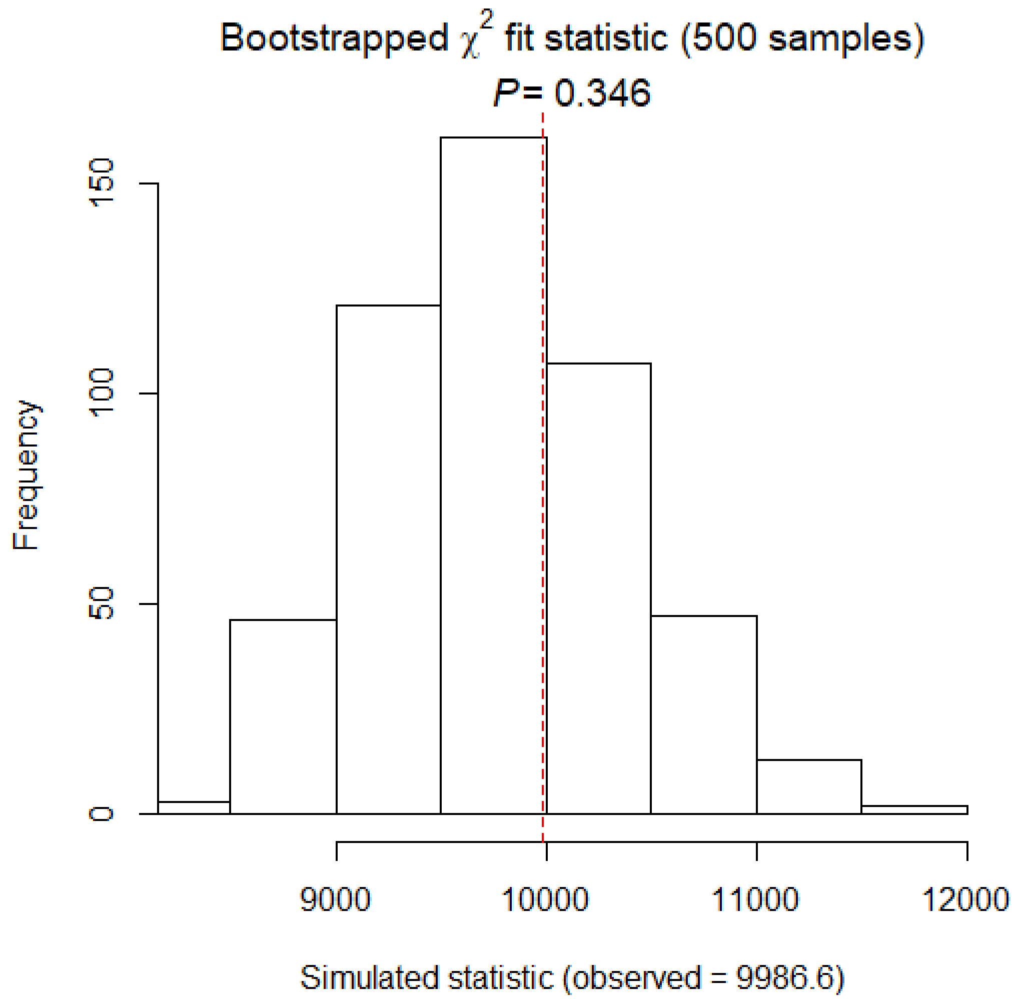

Figure 1. Predicted local abundance estimates with standard error per point count site (0.31 km^2) for dusky grouse in FWP regions 1-5. The estimates are from our top model, a single-season N-mixture model where probability of detection was held constant and local abundance varied among regions.

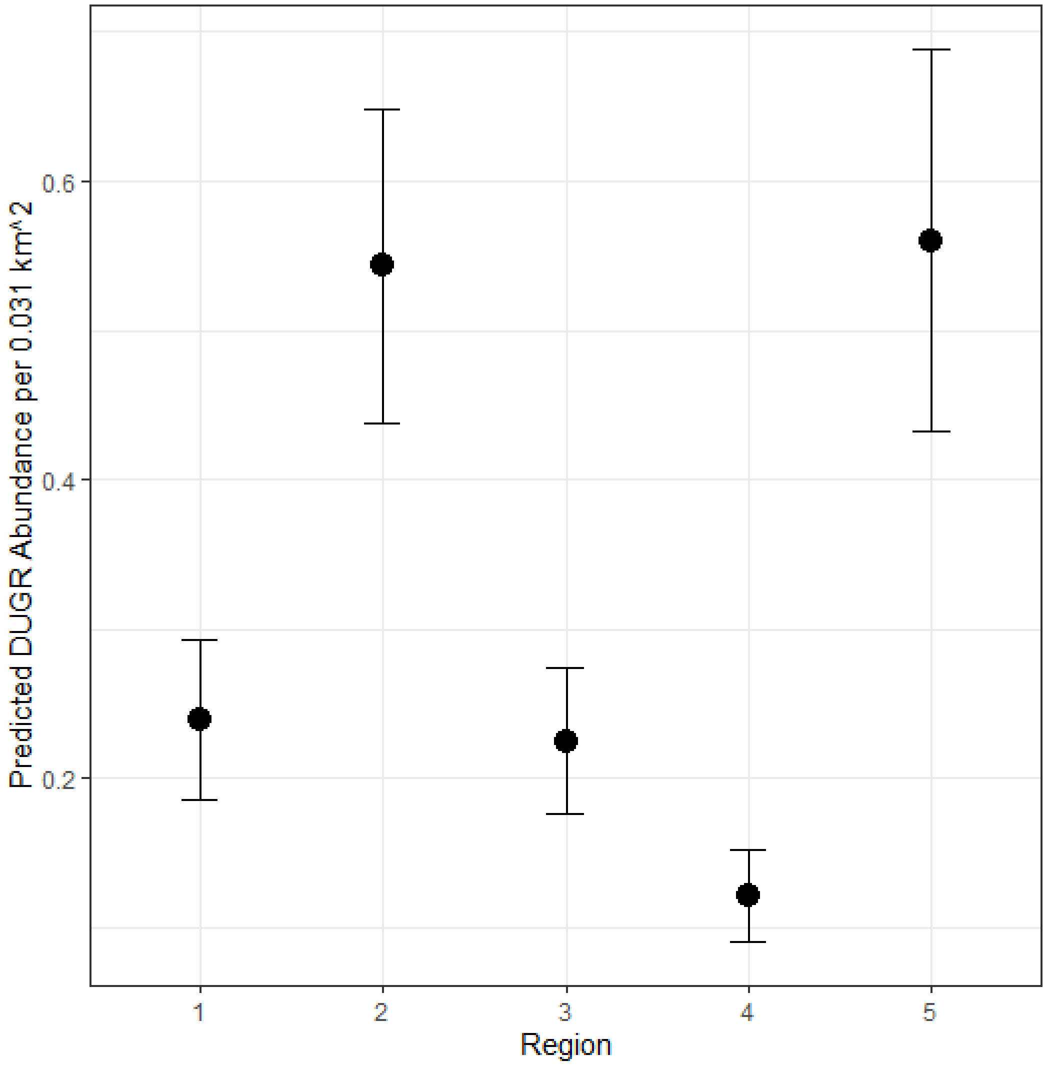

Table 1. Results of simulations evaluating the efficacy of survey protocols using parameters from the 2019 spring pilot study. Mean (95% credible interval) for bias and coefficient of variation from 400 simulation runs for each suite of parameters. Simulations 1-3 evaluated survey protocols with the high estimate for abundance from spring 2019 data. Simulations 4-11 evaluated survey protocols with an estimate of abundance from spring 2019 surveys using electronic playback. R = number of survey sites, J = number of replicate visits, λ = mean abundance per site, p = mean detection probability; CV = coefficient of variation for total population size (Total N) and N.site = estimated number of dusky grouse per survey site. Convergence errors = model convergence errors for estimated number of dusky grouse per survey site. The number of convergence errors was not initially recorded and thus is not available for all simulations; the current classification of yes – many or few is based on personal observation.

	Simulation Parameters				**Bias in λ**	**Bias in *p***	**Bias in Total N**	**Bias in N.site**	**CV Total N**	**Probability CV N.total > 0.15**	**Protocol meets Management Requirements**	**Convergence Errors**
	R	**J**	**λ**	***p***								
Sim 1	100	6	0.48	0.28	0.02 (-0.12, 0.17)	-0.00 (-0.07, 0.07)	1.96 (-7.05, 13.97)	0.02 (-0.07, 0.14)	0.13 (0.09, 0.18)	0.20	no	yes - many
Sim 2	100	8	0.48	0.28	0.01 (-0.11, 0.16)	0.00 (-0.05, 0.06)	0.79 (-5.80, 7.80)	0.01 (-0.06, 0.08)	0.09 (0.06, 0.11)	0.00	yes	yes - many
Sim 3	100	9	0.48	0.28	0.01 (-0.11, 0.14)	-0.00 (-0.05, 0.04)	0.90 (-4.75, 6.78)	0.01 (-0.05, 0.07)	0.08 (0.06, 0.10)	0.00	yes	yes - many
Sim 4	100	8	0.36	0.28	0.01 (-0.10, 0.11)	-0.00 (0.05, 0.05)	0.85 (-3.96, 6.47)	0.01 (-0.04, 0.06)	0.09 (0.07, 0.13)	0.02	yes	yes - many
Sim 5	100	9	0.36	0.28	0.01 (-0.10, 0.13)	-0.00 (-0.06, 0.05)	0.8 (-3.70, 5.70)	0.01 (-0.04, 0.06)	0.08 (0.06, 0.11)	0	yes	yes - many
Sim 6	150	6	0.36	0.28	0.02 (-0.09, 0.12)	-0.00 (-0.06, 0.06)	2.01 (-7.18, 12.75)	0.01 (-0.05, 0.09)	0.11 (0.08, 0.14)	0.04	yes	yes - many
Sim 7	150	8	0.36	0.28	0.01 (-0.08, 0.10)	-0.00 (-0.05, 0.05)	0.76 (-4.14, 7.47)	0.01 (-0.03, 0.05)	0.07 (0.05, 0.09)	0	yes	yes - many
Sim 8	180	6	0.36	0.28	0.01 (-0.09, 0.10)	0.00 (-0.05, 0.06)	0.86 (-8.28, 11.59)	0.00 (-0.05, 0.06)	0.09 (0.07, 0.12)	0.01	yes	yes - many
Sim 9	300	4	0.36	0.28	0.00 (-0.08, 0.10)	0.00 (-0.06, 0.07)	1.92 (-17.13, 24.09)	0.01 (-0.06, 0.08)	0.12 (0.09, 0.16)	0.08	yes-ish	few
Sim 10	360	4	0.36	0.28	0.01 (-0.06, 0.09)	0.00 (-0.05, 0.06)	2.84 (-17.50, 26.25)	0.01 (-0.05, 0.08)	0.11 (0.08, 0.14)	0.02	yes	few
Sim 11	200	6	0.36	0.28	0.01 (-0.07, 0.11)	-0.00 (-0.06, 0.05)	1.78 (-7.85, 12.14)	0.01 (-0.04, 0.06)	0.09 (0.07, 0.12)	0.01	yes	few

* Table is printed here as an image in order to fit the page; a spreadsheet of this table is available in the provided supplemental materials.

Table 2. Summary of spring 2020 survey site data for each FWP regions 1-5. The observed total population is the total number of dusky grouse observed or detected during the surveys. The maximum number of observed dusky grouse from the 4 repetitions from each survey site was used to calculate total observed population. The number of sites and percent of sites where dusky grouse were observed is presented, but dusky grouse could have been present at other survey sites and not been detected.

Region	# of Survey Points	Observed total population	# of sites where observed	% of sites where observed
Region 1	354	44	37	10.5
Region 2	384	102	79	20.6
Region 3	391	47	37	9.5
Region 4	384	26	25	6.5
Region 5	231	57	41	17.4

Table 3. The maximum number of dusky grouse observed at each survey site over the four repetitions for FWP regions 1-5.

Region	The maximum number of dusky grouse observed at each survey site				
	0	1	2	3	4
Region 1	317	31	5	1	0
Region 2	305	62	11	6	0
Region 3	354	27	10	0	0
Region 4	359	24	1	0	0
Region 5	190	34	2	1	4

Table 4. Average number of dusky grouse detected per point count survey during the 2020 spring survey period for each FWP region survey (Regions 1-5).

Region	Average	Standard Deviation
Region 1	0.12	0.39
Region 2	0.27	0.59
Region 3	0.12	0.40
Region 4	0.07	0.26
Region 5	0.25	0.66

Table 5: Support for candidate models predicting abundance and probability of detection using N-mixture models. Three different abundance distributions were examined: negative binomial distribution, zero-inflated poisson distribution, and poisson distribution. A null models indicates a model fitted with constant probability of detection and constant abundance.

Model	**K**	**AICc**	**Δ AICc**	w_i
Null model, Negative Binomial	3	2834.91	0.00	1.00
Null model, Zero Inflated Poisson	3	2863.13	28.22	0.00
Null model, Poisson	2	2973.15	138.24	0.00

Table 6: Support for candidate models predicting abundance and probability of detection using N-mixture models and covariates for abundance. Region refers to FWP region. Surveys occurred in Regions 1-5. Type refers to the whether the transect was on a road or a trail. Habitat suitability refers to the habitat suitability model (see Annual Report 2018) and is either medium-high or high probability of use by dusky grouse.

Model	**K**	**AICc**	**Δ AICc**	w_i
Detection constant ~ Abundance vary by Region	7	2793.69	0.00	1.00
Detection constant ~ Abundance vary by Type	4	2816.52	22.83	0.00
Detection constant ~ Abundance vary by Habitat Suitability	3	2834.91	41.23	0.00
Detection constant ~ Abundance constant	4	2836.86	43.17	0.00

Table 7. Parameter estimates for local abundance (lambda) and probability of detection (*p*) for spring 2020 dusky grouse survey data. Parameter estimates are from the top model in the model set, which was where detection was held constant and abundance varied by region.

Region	**Local Abundance**	**SE**	**95% CI**	***p***	**SE**	**95% CI**
1	0.24	0.05	0.15, 0.37	0.21	0.03	0.20, 0.40
2	0.54	0.11	0.37, 0.79	0.21	0.03	0.20, 0.40
3	0.22	0.05	0.15, 0.34	0.21	0.03	0.20, 0.40
4	0.12	0.03	0.07, 0.20	0.21	0.03	0.20, 0.40
5	0.56	0.13	0.36, 0.88	0.21	0.03	0.20, 0.40

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